KOMTEKINFO JOURNAL
LPPM Universitas Putra Indonesia YPTK Padang
Jl. Raya Lubuk Begalung, Padang, West Sumatera, Indonesia, Zip Code: 25221
Volume: 12, Issue: 3, Page: 176 - 182, September 30th, 2025, e-ISSN: 2502-8758
Available online at website: https://jkomtekinfo.org/ojs/index.php/komtekinfo

Utilization of Convolutional Neural Network Method in Customer Identification Based on Facial Images

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Abstract

Artificial intelligence-based facial recognition technology, especially using the Convolutional Neural Network (CNN) method, is increasingly widespread in various business applications, such as customer data management. This technology allows the system to recognize and identify individuals automatically through facial images, so it is very potential to be applied in customer management. This study aims to implement CNN technology in automatically identifying old customers in a case study in JAVApace Studio. CNN method for facial recognition, optimizing the accuracy of old customer identification, designing CNN system integration in computer vision-based applications, and measuring CNN performance in real-time facial identification. The research method was carried out using a quantitative approach through data collection stages in the form of 875 customer facial images taken in JAVapace Studio, data preprocessing (cropping, resizing, and data augmentation), dataset division for training, validation, and testing. The CNN model used is the ResNet-50 architecture with fine-tuning techniques and freezing layers to improve training efficiency. Model performance evaluation uses a confusion matrix with accuracy, recall, and precision metrics. The results show that the CNN-based facial recognition system achieved 95.7% accuracy in distinguishing existing customers from the test data used. The recall rate was 94.5%, while the precision rate reached 96.2%. The discussion of the results also indicates that the fine-tuning approach is effective in optimizing model performance with an inference time suitable for real-time implementation needs. This study confirms that the implementation of CNN with ResNet-50 architecture is effectively able to recognize the faces of old customers with high levels of accuracy, recall, and precision, making it the right solution in managing customer data automatically and efficiently.

Keywords: CNN, facial recognition, customer identification, computer vision, ResNet-50

1. Introduction

Customers in every organization are the most important asset of any business, as the sustainability and growth of the business greatly depend on the company's ability to maintain and build long-term relationships with its customers [1]. Customer loyalty is an indicator that not only enhances retention but also significantly contributes to the long-term profitability of the Company [2]. The cost of retaining old customers is much lower than acquiring new customers, making customer relationship management (CRM) a priority for modern businesses [3].

In an increasingly competitive ecosystem, a personal and efficient customer experience has become a key differentiating factor between one company and another. Today's customers demand a fast, responsive, and seamless service process, including during the identification and verification of personal data at service locations [4]. In practice, the process of identifying long-term customers that is still done manually has the potential to cause various problems, such as long queues, recording errors, and a less pleasant experience for customers [5]. Rapid and accurate customer identification has become a primary challenge, especially in the context of modern business that demands efficiency and convenience. Traditional identification systems often result in queues, are time-consuming, and are prone to recording errors. This reality drives the adoption of digital technology, including biometrics such as facial recognition, to support customer loyalty-based services [6]. Facial recognition has been widely used in various applications for security, such as biometric door lock security, as well as consumer security for facial recognition systems that unlock locked mobile phones. Object recognition technology has immense potential in the era of Society 5.0 as all industry players are moving towards artificial intelligence [7].

For the past 10 years, Artificial Intelligence (AI) has been a fundamental foundation of digital transformation

Submitted: 25-07-2025 | Revised: 15-08-2025 | Accepted: 10-09-2025 | Published: 30-09-2025

across various industrial sectors. AI is a branch of computer science that focuses on the creation of systems capable of performing tasks that previously required human intelligence, such as reasoning, learning, decision-making, and visual perception [8]. The rapid development of AI has driven the emergence of intelligent solutions that can support businesses in enhancing efficiency and accuracy, as well as creating adaptive and personalized customer experiences [9]. One of the most extensive applications of AI is in the field of computer vision, which enables computers to analyze, understand, and interpret visual data such as images and videos [10]. Computer vision is now widely used in security applications, healthcare, transportation, and customer service based on biometric identification. The use of AI technology in customer identification systems creates significant opportunities to enhance the speed and security of contactless verification, as well as to drive innovation in data-driven services[11].

One of the most important breakthroughs in the application of AI is the Convolutional Neural Network (CNN). The Convolutional Neural Network (CNN) is a popular deep learning architecture in digital image processing [12] . CNN are designed to automatically and adaptively extract important features from images or visual data through convolution and pooling processes, generating effective feature representations for various pattern recognition tasks[13]. CNN is a multilayer artificial neural network specifically optimized to handle two-dimensional data such as images, with a main structure consisting of convolutional layers, activation layers (ReLU), and pooling layers. These layers gradually extract features from simple (e.g., edges, corners) to complex (e.g., face shapes), making it highly effective in detecting and recognizing visual objects [14]. The advantage of CNN over classical methods lies in its ability to manage variations in pose, lighting, and expression in images, and it does not require manual feature engineering [15]

Various studies have shown that CNN serves as the primary foundation for the development of Computer Vision systems, particularly for applications in face detection and recognition. CNN algorithms have also been integrated with cutting-edge technologies, such as transfer learning and augmentation, to enhance the accuracy and efficiency of processing large-scale facial image data [16]. One of the factors why facial recognition is preferred over the use of fingerprints or retina scans is because it is easier to use, and the scope of application for facial recognition systems is also broader, including areas such as security, surveillance, public identity verification, criminal justice systems, image database investigations, smart card applications, multimedia, and video indexing [17] .

Facial recognition systems are the most challenging biometric technique due to the high variation of faces that exist. Some of these variations include head pose, age, occlusion, lighting conditions, and facial expressions [18]. One of the advantages of using deep learning is its ability to be trained with such large datasets, which leads to the discovery of the best features for representing the data. CNN is widely used in facial analysis and classification, such as gender, age, and expression classification. For gender classification, CNN performs exceptionally well, achieving an accuracy of 97% [19]. With a different architecture, CNN can achieve an accuracy of up to 98.75% [20]. Previous research has demonstrated the effectiveness of CNN methods in facial recognition systems. The study conducted by Baareh (2024) utilized a lightweight CNN architecture with 16 layers on the FEI dataset, achieving a training accuracy of 97.73% and a testing accuracy of 83.33%, reflecting good performance yet leaving room for improvement in the model's generalization capability. [21].

In subsequent research, the developed CNN model for the facial attendance system was able to achieve a training accuracy of 97%, a validation accuracy of 90%, and a testing accuracy of 93%, which underscores the potential of this method to support the signaling and security of the attendance process [22]. The face detection and recognition system based on YOLOv8 and ResNet-50 tested on three groups achieved an average accuracy of 85.26%, with a detection accuracy rate reaching 95.46% [23]. Various studies have applied Convolutional Neural Networks (CNN) for a range of face recognition needs, such as smart home authorization, employee and student attendance, and deepfake face detection.

This research presents a distinct and unique contribution compared to previous studies. Specifically, this study designs a system for identifying long-term customers in a photography studio environment, not merely for attendance or security purposes, but to genuinely support customer loyalty and experience. The CNN model employed implements fine-tuning on the pre-trained ResNet-50 architecture and systematically applies augmentation techniques and layer freezing to address data limitations, an approach that has not been widely explored in the context of photography studio business customers. The evaluation is conducted comprehensively, not only regarding accuracy but also considering overfitting analysis, inference speed, and optimization recommendations for large-scale implementation. So, this research is expected to be a handy reference for customer service automation innovations using computer vision, especially for small and medium-sized businesses. Applying a CNN based on the ResNet-50 architecture with fine-tuning strategies and data augmentation can really boost the accuracy of identifying returning customers in a photography studio, even when there's not a lot of data.

2. Research Methodology

Research methodology is a systematic process used to collect, analyze, and interpret data in order to answer research questions or solve problems. The research methodology provides a framework and systematic procedures that researchers use to collect, analyze, and present data in a valid manner. The identification process in this research can be illustrated within the research framework. The depiction of this framework is presented in Figure 1.

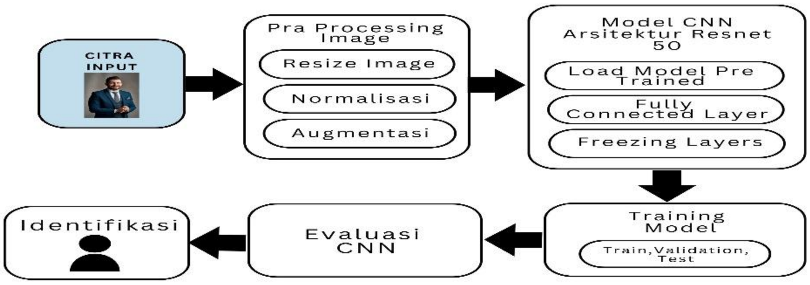

Figure 1. Research Framework

This image illustrates the workflow of a facial recognition system using the CNN architecture method of ResNet-50 to identify returning customers. The process begins with input images obtained from a camera or a database, followed by preprocessing stages such as resizing, normalization, and augmentation to ensure data quality. Subsequently, the images are processed by the ResNet-50 model, which is loaded from a pre-trained model, fine-tuned at the fully connected layers, with several layers omitted to retain the initial weights. The model is then trained with the training data, validated, and tested. The training results are evaluated through accuracy metrics and model performance, and are then used to automatically recognize returning customers.

2.2.Preprocessing Data

The acquired images are then selected for their suitability as sample images. After data acquisition and sorting, the next step is to perform data preprocessing using image processing applications.

a. Cropping: Performing image cutting to eliminate unnecessary parts. This is intended to reduce the dimensions of the image and shorten computation time.

b. Resize: Adjusting the image size to standard dimensions (224×224 pixels)

c. Data Augmentation: This is performed to increase the diversity of data, including techniques such as rotation (90°, 180°, 270°), as well as zoom-in and zoom-out, to enhance the generalization of the model.

2.3 Training Model Resnet-50

The CNN model with a ResNet-50 architecture was utilized as the basis for implementation. The training strategy was conducted using fine-tuning techniques with pre-trained weights from the ImageNet dataset. Most of the initial layers in ResNet-50 were frozen, while several of the final layers and fully connected layers were retrained to identify customer faces.

In the ResNet architecture, there's a tweak in the shortcut connection block. This mod involves stacking the results from the shortcut connection with three convolution layers called a residual block, with each layer being sized 1x1, 3x3, and 1x1. This modification is known as the Deeper Bottleneck Architecture, where the last convolution layer is used to reduce and increase dimensions while skipping the 3x3 convolution layer from smaller input/output. For ResNet architectures like 50, 101, and 152 layers, they use parameter-free identity shortcuts.

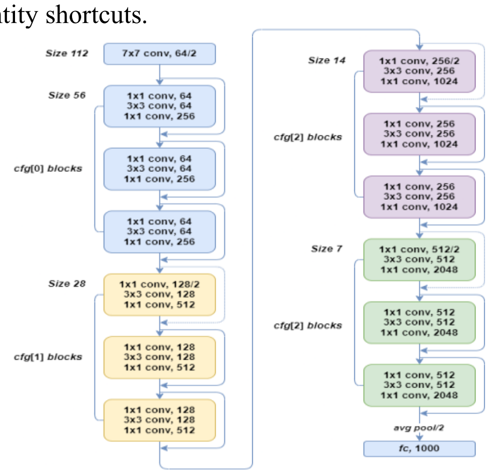

Figure 2. ResNet Architecture

2.2 Arsitektur CNN

Convolutional Neural Network (CNN) is a type of deep learning model capable of processing data in the form of grid patterns [24]. Convolutional Neural Networks (CNN) are specifically designed to process multidimensional data such as images and videos. CNNs are capable of automatically extracting important features from the input data through multi-layer convolutional layers. Generally, the architecture of CNN consists of several main types of layers, namely convolutional layers, pooling layers, flattening layers, and fully connected layers..

1. Convolution

Convolution is the total sum of the product of each corresponding element (having the same coordinate position) in two matrices or two vectors. In the architecture of convolutional neural networks (CNNs), convolution plays a key role in feature extraction from input data. Convolution is an operation that involves two functions or matrices: the input function and the filter (or kernel).

2. ReLu Activation

The rectified linear unit, commonly known as ReLU, is the most common and fundamental method to introduce non-linearity into neural networks. This function is defined as max(0, x). ReLU is a highly effective activation function that is widely used across various neural network architectures due to its simplicity and its ability to better support the training of deeper networks. ReLU is easy to compute as it only requires a simple comparison, making it highly efficient for computation.

3. Pooling

Pooling is the process of reducing the size of an image data. In image processing, pooling also aims to enhance the positional invariance of features, as well as to accelerate computation and control the occurrence of overfitting. There are two techniques of pooling, namely Max Pooling and Average Pooling. Max Pooling aims to find the maximum value within a certain area, while Average Pooling seeks to find the average of the features within that area.

4. Confusion Matrix

The confusion matrix is one of the methods used to evaluate classification methods. The confusion matrix provides detailed information on how the model classifies data and helps in understanding where the model may make errors. Typically, the confusion matrix for binary classification problems (two classes) has a 2x2 format, but it can be extended to classification problems with more than two classes.

Tabel 1 Term Confusion Matrix

	Positive Prediction	**Negative Prediction**
Positive Actual	True Positive (TP)	False Negative (FN)
Negative Actual	False Positive (FP)	True Negative (TN)

The calculation of precision value can be done using Equation 1.

$$Precision = \frac{TP}{(TP+FP)} \quad (1)$$

Equation 1 represents the calculation of the average precision value, which is derived from the classification data indicating how many data points are correct in relation to the actual values. With the predictions provided by the system, precision measures how well the classification model identifies the true positive class from all the positive predictions made. To understand this equation in more detail, let us examine how precision is calculated and averaged. The calculation of the recall value can be performed using Equation 2.

$$Recall = \frac{TP}{(TP+FN)} \quad (2)$$

Equation 2 represents the calculation of the average recall value, which indicates how many of the correct data points are identified in the classification results. Recall (also known as Sensitivity or True Positive Rate) measures the model's effectiveness in detecting all positive instances from the actual class. In multi-class classification, recall is computed for each class and then averaged. Let us further discuss recall and its calculation methods. The accuracy value can be calculated using Equation 3.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

Equation 3 represents the calculation of the average accuracy value to indicate the level of effectiveness per class of a classification [19]. Recall (also known as Sensitivity or True Positive Rate) measures how well the model detects all positive instances from the actual class. In multi-class classification, recall is calculated for each class and then averaged. Let us discuss further about recall and its calculation methods. The FScore value can be calculated using Equation 4.

$$F1 = \frac{2(P.R)}{(P+R)} \quad (4)$$

Equation 4 represents the calculation of the average F-score value, which is a combination of the calculations of recall and precision [20]. The F-score, or F1-score, is an evaluation metric that combines precision and recall into a single value. The F1-score provides a single measure that reflects the balance between precision and recall, and is extremely useful.

3. Results and Discussion

This research produces a facial recognition system based on Convolutional Neural Network (CNN) with a ResNet-50 architecture optimized for identifying long-time customers at JavaPace Studio. The dataset consists of 875 images of long-time customers taken during the period from January 2024 to March 2025.

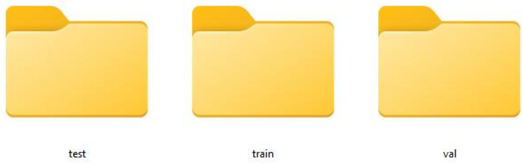

Figure 3. Results of dataset split

The dataset is divided into three main parts to optimally support the training process of the CNN model. The largest part is the training set, which comprises approximately 70–80% of the total data and is used to train the parameters of the CNN model. Next, a validation set of about 10–15% is utilized to monitor and evaluate the model's performance during the training process to prevent overfitting. Finally, the test set, also comprising around 10–15%, serves to assess the final performance of the model after the training process is completed, ensuring that the model has good generalization to new data.

All images undergo a preprocessing stage that includes face area cropping, resizing to dimensions of 224×224 pixels, color conversion (RGB/Grayscale), and augmentation (rotation and zoom) to enhance data diversity. The resulting cropped images can be presented in Figure 4.

Figure 4. Result of the cropped face image

Based on the architecture of the CNN method, a search for calculations of the CNN method can be conducted based on customer data. The pixel values of the face are presented in Table 2.

Table 2. Customer Face Pixel Values

100	110	120	115	105
90	105	115	125	110
80	95	100	105	90
70	85	90	95	85
60	70	75	80	70

The kernel convolution process is performed by sliding the kernel over the input image, and at each position, an element-wise multiplication operation is carried out between the pixel values of the image and the kernel values. The results are then summed to produce a single pixel value on the feature map. The results of the convolution values are presented in Table 3.

Table 3. Customer Face Convolution Values

-1	0	1
-1	0	1
-1	0	1

The training process of the CNN model with ResNet-50 architecture was conducted over 11 epochs using a customer face dataset. The data was divided into a training set (70%) and a validation set (30%) to monitor the model's generalization capabilities. The training results indicate that the training accuracy gradually improved from 0.18 in the initial epoch to around 0.32 by the 10th epoch, with the loss value decreasing from 2.30 to 1.83. This signifies that the model successfully learned patterns from the training data progressively. After going through the epoch stages, the results of the testing will appear as shown in Figure 5.

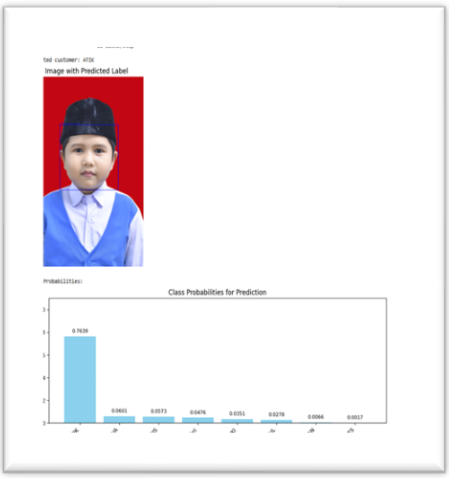

Figure 5. Test Results

Figure 5 displays the prediction results of the CNN-based facial recognition system using the ResNet-50 architecture on a test image. The model performs facial feature extraction and matches it with a pre-trained identity database. Based on the inference process, the system pr edicts that the image belongs to the class "ATIK", meaning the model recognizes the face in the image as an individual labeled ATIK in the dataset.

The training accuracy reached 95.7% in differentiating between existing customers from the test data used. The recall rate obtained was 94.5%, while the precision rate reached 96.2%

4. Conclusions

This research successfully implemented a customer identification system based on Convolutional Neural Network (CNN) with an optimized ResNet-50 architecture using fine-tuning, layer freezing, and data augmentation techniques to improve accuracy on limited datasets. The system is capable of recognizing customers at JavaPace Studio with an accuracy rate of 95.7%, a recall rate of 94.5%, and a precision rate of 96.2%. These results demonstrate that the approach used is effective in minimizing identification errors and fulfilling the needs of real-time facial recognition. The successful implementation of this model proves that the combination of ResNet-50 architecture with appropriate optimization strategies can be a reliable solution for customer service automation, especially for small and medium enterprises that require speed, efficiency, and high accuracy in managing customer data.

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